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Implementation of Time Series Forecasting for Inflation Prediction in Indonesia

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Abstract

Inflation is a crucial macroeconomic indicator that reflects economic stability and influences sectors such as consumption, investment, and policy-making. This study aims to implement and compare three time series forecasting models: Seasonal Autoregressive Integrated Moving Average (SARIMA), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) to predict inflation in Indonesia. The study utilizes monthly inflation data from Bank Indonesia (2003–2024) and Consumer Price Index (CPI) data from Statistics Indonesia (2003–2019). Model performance is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results indicate that SVR achieves the best performance in predicting inflation, with MAE of 1.53, MSE of 2.72, and RMSE of 1.64, demonstrating its effectiveness in capturing nonlinear patterns. Meanwhile, SARIMA provides the most accurate predictions for CPI, with MAE of 11.55, MSE of 191.76, and RMSE of 13.84. LSTM shows competitive performance but is less consistent compared to the other models. These findings highlight the importance of selecting appropriate models based on data characteristics to improve forecasting accuracy and support economic decision-making.

Keywords: Consumer Price Index, Forecasting Model, Inflation, Time Series Forecasting

1. INTRODUCTION

Every nation aims to promote economic expansion as a means of enhancing societal well-being. The process of raising per capita production over an extended period in a sustainable way is known as economic growth [1]. One of the key prerequisites for attaining progress and well-being is this indicator, which shows the state of a nation's economy [2]. Inflation is one metric that is frequently used to quantify and examine economic progress. Inflation is a worldwide occurrence that affects many different industries in both developed and developing nations [3]. Countries' rates of inflation differ greatly from one another, based on variables including political stability, economic circumstances, and monetary policy [4].

Inflation is a condition in which the overall prices of goods and services increase continuously over time. This condition does not only occur in one type of goods but covers a wide range of goods and services [5]. At low and stable levels, inflation can provide benefits to the economy such as encouraging consumption and investment growth. However, if inflation is at a high level, it can create uncertainty that inhibits investment activities, suppresses consumption, and weakens the competitiveness of domestic exports [6]. Uncontrolled inflation also risks causing inefficient resource allocation and increasing poverty. Therefore, controlling inflation is one of the main challenges for economic authorities and central banks in maintaining price stability while ensuring sustainable economic growth [7].

Inflation has a significant impact on society and the business world. For the public, inflation reduces purchasing power, especially for lower economic groups who are vulnerable to declining real income. This condition can increase their burden of living [8]. Meanwhile, for businesses, the inflation rate is an important factor in making business decisions. High and unstable inflation creates uncertainty that makes it difficult for economic actors to plan consumption, production, and investment [9]. This instability hinders decision-making, depresses the value of the currency, and slows overall economic growth [10]. In addition, the education sector is also affected by inflation. Rising economic costs result in higher education costs, which is a heavy burden for middle and lower-income earners. This demonstrates that inflation has an impact on society as a whole as well as the economy [11]. Thus, forecasting inflation is a calculated move that helps preserve price stability and encourage long-term economic expansion. One commonly used method in inflation forecasting is time series forecasting, which allows for the analysis of patterns, trends, and variations in historical data to produce more accurate projections [12]. With this approach, the government, businesses, and the public can be better prepared for economic dynamics and design effective mitigation strategies to reduce the negative impact of inflation.

This study is based on research by Rizki and Taqiyyuddin (2021) that uses the SARIMA model to analyze Indonesia's inflation rate. Monthly inflation data from Bank Indonesia (BI) from January 2003 to November 2020 was analyzed in this study. This study uses the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and concludes that the best model is SARIMA(1,0,1)(1,1,1), which is determined by the Akaike Information Criterion (AIC) being low and the Mean Absolute Percentage Error (MAPE) being about 5.19 percent. The study's findings indicate that this model has a good accuracy rate in predicting Indonesia's inflation rate [13]. Continuing the investigation, this study compares the most recent monthly inflation statistics from BI through August 2024 with Consumer Price Index (CPI) data from the Central Bureau of Statistics (BPS). The SARIMA model is used in this study together with Support Vector Regression (SVR) and Long Short-Term Memory (LSTM). Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are used for assessment. It is anticipated that this strategy will increase the accuracy of inflation predictions and deepen understanding of how time series forecasting techniques may be used for inflation analysis.

2. MATERIALS AND METHOD

The research methodology aims to design, implement, and evaluate prediction projects with a structured and systematic approach. The steps taken in the research are presented in Figure 1.

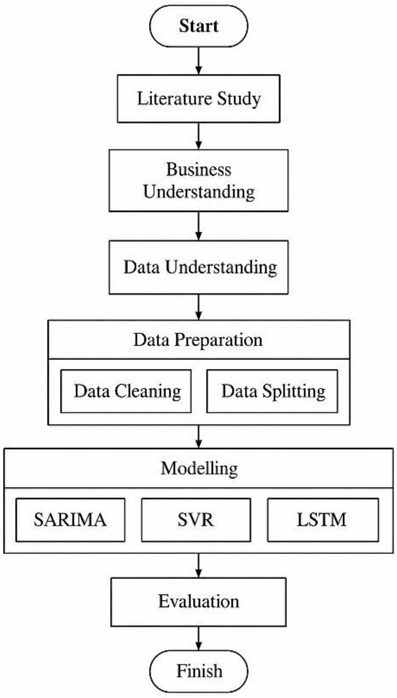

Figure 1. Research Methodology

The first step begins with a literature study, followed by collecting inflation data from BI and CPI data from BPS. After the data is collected, pre-processing and data division are carried out using the hold-out technique. Modeling is done using three algorithms, namely SARIMA, SVR, and LSTM. Furthermore, the prediction process is carried out, comparison of prediction results with actual values, and evaluation of model performance using MAE, MSE, and RMSE metrics to assess the quality of predictions in the future period. The following data visualization is shown in Figure 2 and Figure 3.

2.1. Inflation

In general, inflation is defined as a long-term, consistent rise in the average cost of goods and services [14]. When inflation occurs, the value of the currency decreases as prices rise, which in turn reduces people's purchasing power. This happens because the amount of money circulating in society is not keeping pace with rising prices. Inflation is measured through price indices, such as the CPI [15].

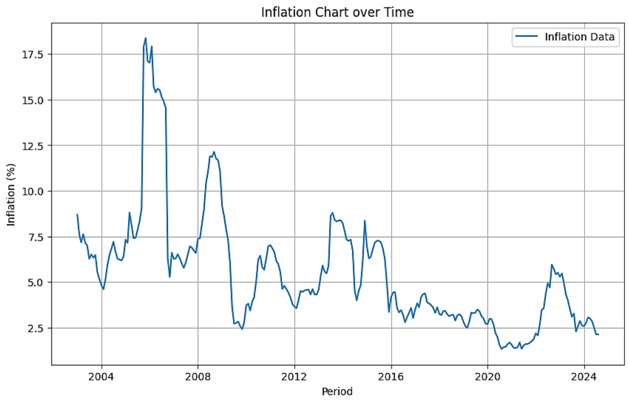

Figure 2. Indonesian Inflation Data (2003 – 2024)

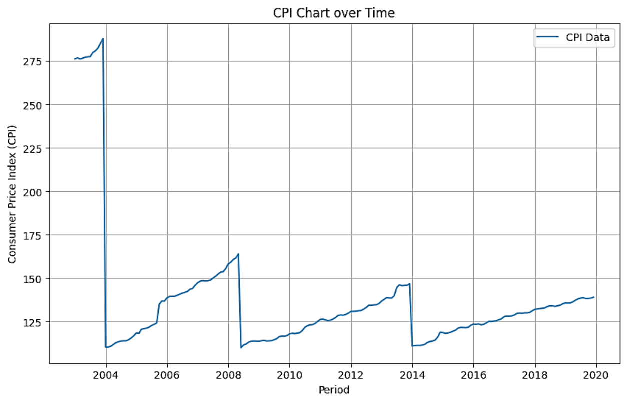

Figure 3. Indonesian CPI Data (2003 – 2019)

2.2. Time Series

A statistical method for forecasting future trends from historical data, time series is helpful when making decisions [16]. This method assumes that past events have an impact on present occurrences by studying a particular object at a given time, such as daily, weekly, monthly, or annually. Time series analysis is used in a variety of domains, including social, financial, environmental, and economic ones, to identify recurring patterns to comprehend trends, patterns, and relationships between data [17]. The properties of the data patterns which are typically classified into four primary categories: horizontal (H), seasonal (S), cyclical (C), and trending (T) patterns determine which time series method is best [18].

2.3. Seasonal Autoregressive Integrated Moving Average (SARIMA)

SARIMA is an extension of the ARIMA model used for time series data with seasonal patterns, which was introduced in the 1970s by George Box and Gwilym Jenkins [19]. It models time series data with recurring periodic patterns, such as annual or monthly, characterized by the regular appearance of strong correlations [20]. The seasonal SARIMA or ARIMA model is usually represented with the (p,d,q)(P,D,Q) notation described by Equation 1.

$$\varnothing_p(B)\varnothing_P(B^s)(1-B)^d(1-B^S)^D X_t=\theta_q(B)\theta_Q(B^s)e_t \tag{1}$$

2.4. Support Vector Regression (SVR)

SVR is an extension of the Support Vector Machine (SVM) designed for regression problems, which aims to produce accurate predictions with low error rates [21]. Unlike SVM which focuses on classification, SVR tries to ensure all the data is within one area while minimizing the epsilon (ε) value [22]. SVR effectively overcomes the overfitting problem that can lead to poor predictions due to models that capture noise or random errors. In the SVR model, the regression function *f(x)* can be expressed as in Equation 2.

$$f(x)=W^T\varnothing(x)+b \tag{2}$$

Where W is an l dimensional weight vector, $\emptyset(x)$ = a function that maps x to a space with l dimensions, and b = a constant bias vector.

2.5. Long Short-Term Memory (LSTM)

A Recurrent Neural Network (RNN) development called LSTM was created to address RNN's shortcomings in terms of long-term data storage [23]. Introduced by Hochreiter & Schmidhuber in 1997, LSTM is superior in managing long sequential data and is specifically used to predict long-term dependencies [24]. LSTM uses a gate mechanism (input gate, forget gate, output gate) to filter and update information in memory cells, thus enabling continuous learning on sequential data [25]. As a subset of Artificial Neural Networks (ANNs) inspired by biological neural systems, ANNs are highly effective in identifying patterns and dynamic relationships between inputs and outputs [26].

2.6. Literature Review

Various studies have discussed time series forecasting using SARIMA, SVR, and LSTM models, each of which shows advantages according to the characteristics of the data used. Ma et al. (2021) optimized the SARIMA model through quantile outlier detection and mean interpolation which successfully improved the accuracy of fire frequency predictions by 11.5% compared to the standard SARIMA model [27]. Rohmah et al. (2021) compared four kernels in the SVR model and found that the Gaussian RBF kernel gave the most accurate CPI prediction results with the lowest MAPE value [28]. Meanwhile, Bhandari et al. (2022) showed that a single LSTM model is more accurate than a multilayer in predicting the S&P 500 index [29]. These three studies confirm the effectiveness of SARIMA, SVR, and LSTM models in time series forecasting according to data characteristics.

In addition to the previously discussed models, several studies have further examined the comparative performance of machine learning and statistical approaches in time series forecasting. For instance, Azani et al. demonstrated that ARIMA tends to perform well on linear and seasonal data, while machine learning models such as SVM and LSTM outperform in capturing nonlinear relationships in energy consumption datasets [24]. Similarly, Abebe highlighted the effectiveness of SARIMA in modeling seasonal temperature and rainfall patterns, emphasizing its robustness in handling periodic fluctuations [19]. These findings strengthen the argument that SARIMA remains a reliable baseline model, particularly when the underlying data exhibit clear seasonal characteristics. However, its limitation in handling nonlinear patterns necessitates the integration or comparison with more flexible models such as SVR and LSTM.

Furthermore, Support Vector Regression (SVR) has gained significant attention due to its strong generalization capability and robustness against overfitting, especially in small and medium-sized datasets. Novianti et al. applied SVR to predict fuel consumption and reported high prediction accuracy due to its ability to model nonlinear relationships efficiently [17]. Likewise, Saadah et al. demonstrated that SVR performs well in forecasting commodity prices and exchange rates, highlighting its adaptability across different economic indicators [18]. These studies indicate that SVR is particularly suitable for economic time series data, where patterns are often nonlinear and influenced by multiple external factors. Consequently, the findings support previous research that identified SVR as a strong candidate for inflation prediction, especially when compared to traditional statistical methods.

On the other hand, deep learning approaches such as LSTM have shown promising results in capturing long-term dependencies in sequential data. Luchia et al. found that LSTM outperformed traditional neural networks and recurrent neural networks in predicting extreme climate changes due to its ability to retain temporal information over long sequences [16]. Similarly, Arfan and ETP reported that LSTM achieved competitive performance in stock price prediction, although its effectiveness depends heavily on data quality and parameter tuning [22]. Despite its advantages, LSTM models often require large datasets and high computational resources, which can limit their practical implementation. Therefore, while LSTM offers superior capability in modeling complex temporal dynamics, its performance must be carefully evaluated against simpler models such as SARIMA and SVR, particularly in datasets with limited size or high volatility.

3. RESULTS AND DISCUSSION

3.1. Business Understanding

This stage aims to understand the research context by collecting monthly inflation data from BI and CPI data from BPS. Inflation data is used to analyze inflation fluctuations, while CPI data serves as a benchmark for a comprehensive picture. The use of data from official sources ensures the reliability and validity of the information for relevant and reliable analysis.

3.2. Data Understanding

This study uses two main datasets to analyze inflation and CPI trends in Indonesia. The inflation dataset includes 260 monthly data from January 2003 to August 2024, while the CPI dataset consists of 204 monthly data from January 2003 to December 2019. Analysis of these two datasets provides insights into economic dynamics, including changes in prices and consumption patterns, which can be used as a basis for formulating more effective economic policies.

3.3. Data Preparation

The next stage is data pre-processing which includes cleaning to remove incomplete or duplicate data, as well as dividing the data into training and testing sets.

3.3.1. Data Preparation

This research converts the “Period” column in the inflation and CPI datasets to a datetime format to improve the accuracy of the analysis and converts the “Inflation Data” column to a numeric format by removing non-numeric characters and handling NaN values to ensure good data quality.

3.3.2. Data Preparation

Furthermore, the dataset is divided into 80% for training data and 20% for testing data, to ensure that the model can be effectively trained without overfitting and has good generalization ability.

3.4. Modeling

3.4.1. Implementation of SARIMA Model

The Inflation dataset's p-value of 0,43 from the Augmented Dickey Fuller (ADF) test suggests that the data is not stationary. The data is stationary after the first differencing, as indicated by the p-value of 2,24. In the meantime, the CPI dataset's ADF test yields a p-value of 0,01, indicating that the data is stationary. Heteroscedasticity is indicated by the p-value of 2,53 obtained from the ARCH Heteroscedasticity test on the inflation dataset. The p-value is 0,99 following logarithmic processing and differencing, indicating stationary data. After transformation, the p-value drops to 0,99, indicating data stationarity in variance, from the same test on CPI, which yields a p-value of 1,93. The information is prepared for additional examination.

Finding the optimal model involves choosing the (p,d,q)(P,D,Q) parameters based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) graph analysis after the inflation and CPI data have been determined to be stationary in mean and variance. To choose the best Autoregressive (AR) and Moving Average (MA) parameters for both seasonal and non seasonal components, ACF and PACF assist in identifying the pattern of interrelationships between data at specific lags. The ACF and PACF graphs for inflation data after differencing are shown in Figure 4.

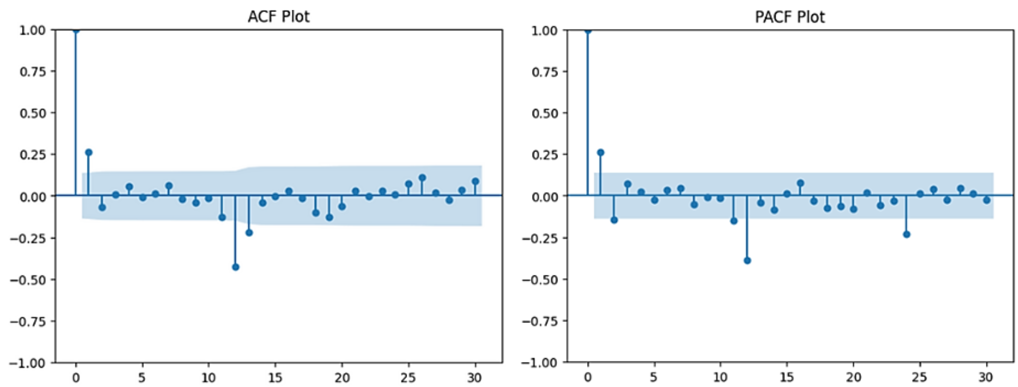

Figure 4. (a) ACF Plot of Inflation, (b) PACF Plot of Inflation

Based on Figure 4, the ACF and PACF analysis shows a significant autocorrelation pattern at lags 1 and 2 for ACF and lag 1 for PACF. This pattern shows that the MA model utilizes q=1, whereas the AR model can use either p=1 or p=2. Upon achieving stationarity through differencing (d=1), the ARIMA (1,1,1) and ARIMA (2,1,1) models emerge as the primary contenders. The AIC value will be used to compare the two models, and the model with the lowest AIC value will be selected as the best. Furthermore, error matrices like RMSE or MAE are used to evaluate accuracy. The ACF and PACF plots for the CPI dataset are presented in Figure 5.

Based on Figure 5, the ACF plot shows a significant autocorrelation at lag 1, which reflects an MA pattern. In the meantime, an AR pattern is reflected in the PACF plot, which displays a strong partial autocorrelation at lag 1. This pattern suggests that the ARIMA (1,1,1) model can manage the trend with parameters AR=1, MA=1, and d=1.

Next, various parameter combinations were tested to determine the best model, where the selection was made based on the AIC value. The model with the lowest AIC value is selected because it shows the optimal balance between accuracy and complexity. The test results show that ARIMA(2,1,1) is superior in modeling inflation, with an AIC value of -189.11, compared to ARIMA(1,1,1) which has a value of -187.15. This difference indicates that the addition of one AR parameter to ARIMA(2,1,1) improves the model's ability to capture the data pattern without adding excessive complexity. Therefore, ARIMA(2,1,1) is chosen as the best model to predict inflation, while ARIMA(1,1,1) remains the optimal model in modeling CPI because it is more in line with the data characteristics.

Next, the SARIMA model is developed based on the best parameters obtained to capture seasonal patterns and trends in the data. Predictions are made using historical data, then their accuracy is evaluated with error matrices such as MAE, MSE, and RMSE to compare the predicted results with actual data. This evaluation ensures the reliability of the model in producing accurate projections. The prediction results and performance analysis of the SARIMA model are presented in Figure 6.

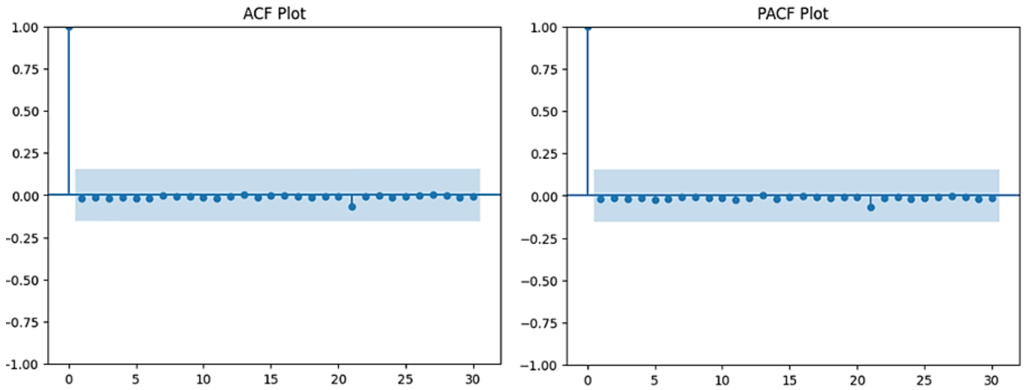

Figure 5. (a) ACF plot of CPI, (b) PACF plot of CPI

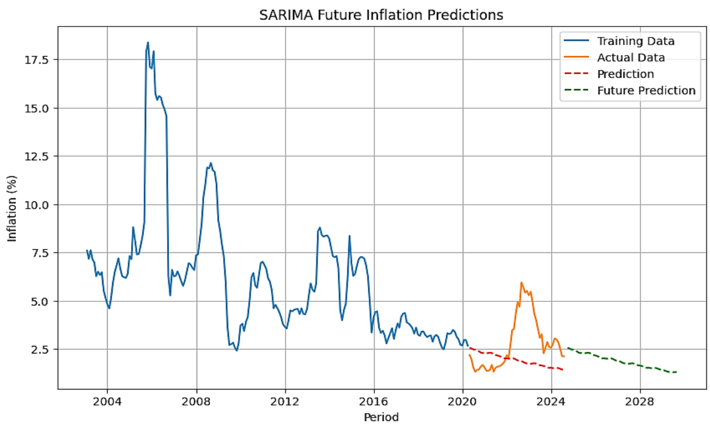

Figure 6. SARIMA Inflation Prediction

Based on Figure 6, inflation in Indonesia experienced significant fluctuations over the period 2003 to 2029. The peak of inflation was recorded at 17.5% in 2006 triggered by the increase in fuel oil prices, followed by a spike of 12% in 2008 due to the global financial crisis. Entering the period 2016 to 2020, inflation tended to stabilize in the range of 2.5% to 3.5%, reflecting the successful implementation of effective monetary policy. Predictions until 2029 show a gradual downward trend towards stabilization at around 2%, reflecting consistent and sustainable inflation control. The next step is to predict the CPI dataset to further analyze the trend. The prediction results can be seen in Figure 7.

Based on Figure 7, the CPI shows a long-term upward trend from 2003 to 2024 although it has experienced sharp declines in some periods. A significant spike occurred in 2004 with the level reaching 275, but the actual data shows a more moderate increase than predicted. Future predictions suggest that the CPI will continue to increase until it reaches a level of around 225 to 240 in 2024.

3.4.2. Implementation of SVR Model

The first step in building the SVR model is to separate the X feature (timestamp) and Y target (inflation), then standardize both using StandardScaler to scale the data uniformly. Hyperparameters C, Epsilon (ε), and gamma are optimized using GridSearchCV with Radial Basis Function (RBF) kernel and cross-validation to pre-vent overfitting. After the optimal parameters are obtained, the SVR model is retrained with standardized training data. The last step is to predict inflation using the best model that has been built. The prediction results can be seen in Figure 8.

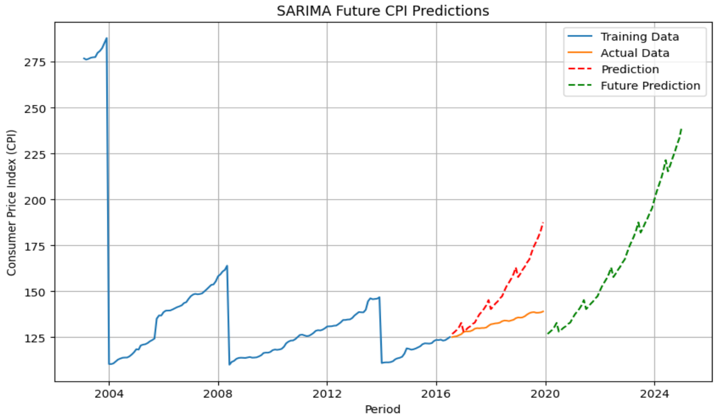

Figure 7. SARIMA CPI Prediction

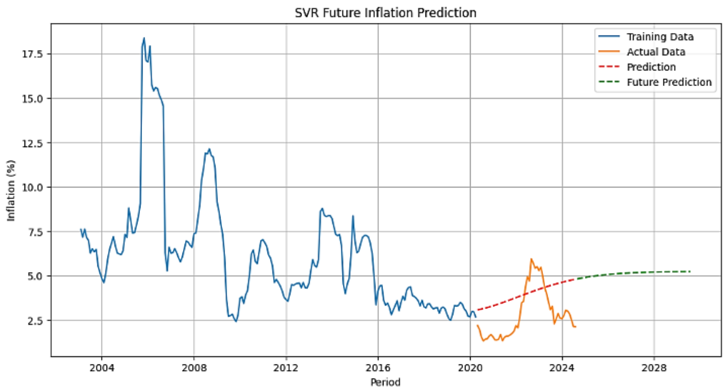

Figure 8. SVR Inflation Prediction

Based on Figure 8, the SVR model's predictions indicate a moderate upward trend in inflation, reaching approximately 5% in 2024, which closely matches the actual data pattern. This suggests that the model is effective in short-term forecasting. Further projections show that inflation will stabilize around 5% through to 2029, indicating a relatively steady economic outlook in the long term. These results reflect the SVR model's ability to capture underlying inflation trends with consistent performance over time. As the next step, the model is applied to forecast the CPI, with the results presented in Figure 9.

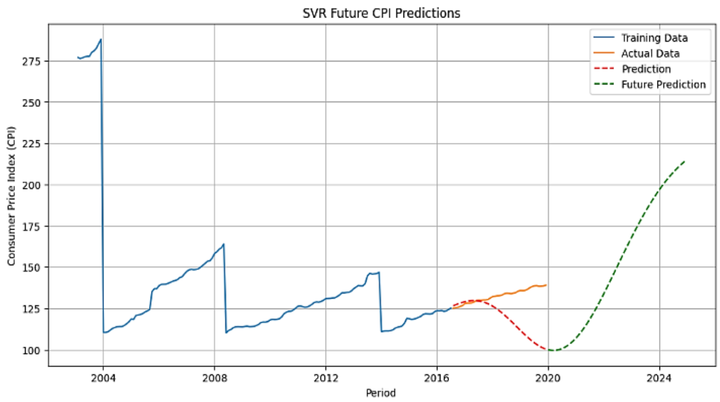

Figure 9. SVR CPI Prediction

Based on Figure 9, the SVR model shows a better ability to predict the upward trend of the Consumer Price Index (CPI) than the other models. In the short term, the SVR predictions show a slight decline, which likely reflects seasonal fluctuations or short-term economic factors. However, in the long term, the model predicts a sharp upward trend, with the CPI projected to reach a range of 215 to 220 by 2024. These results suggest that the SVR can capture CPI growth patterns more accurately, providing clearer insights into the future direction of price movements.

3.4.3. Implementation of LSTM Model

Before being transformed into time sequence and 3D (sample, time step, feature) format, the data were normalized using MinMaxScaler to improve model performance and training efficiency. The LSTM model was constructed using two hidden layers with 50 units, ReLU activation, and dropout to help prevent overfitting and enhance generalization.

The model was trained using the Adam optimizer over 50 epochs with a batch size of 16, ensuring stable and effective learning. After training, predictions on the test data were rescaled to their original scale using inverse transform, so they could be interpreted and compared with actual inflation values. The prediction results are presented in Figure 10.

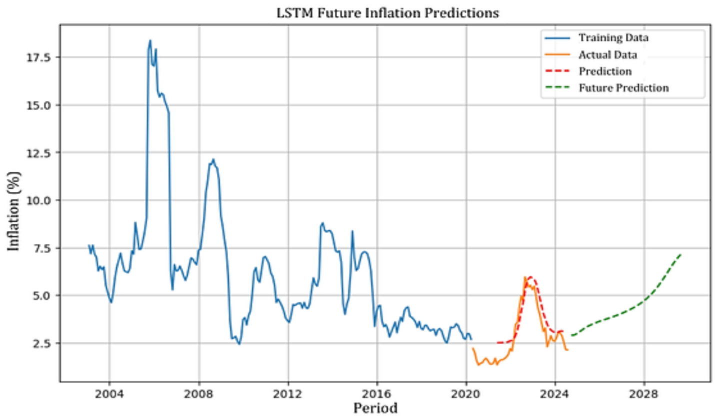

Figure 10. LSTM Inflation Prediction

Based on Figure 10, inflation experienced significant fluctuations from 2003 to 2020, peaking at around 17.5% in 2006 and spiking to 12% in 2008. After a relatively stable period, it rose sharply again to 5.5% between 2022 and 2023. The model's predictions indicate a continued upward trend, with inflation expected to reach approximately 7% by 2029. This highlights potential future economic pressures that may require attention from policymakers. As a follow-up, the model was also applied to forecast the Consumer Price Index (CPI), with the results shown in Figure 11.

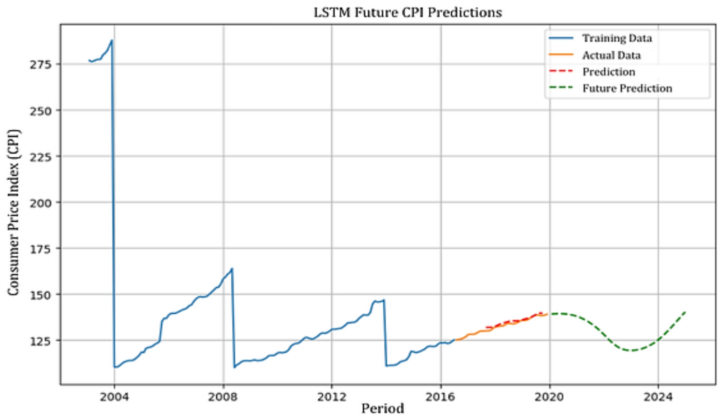

Figure 11. LSTM CPI Prediction

Based on Figure 11, there was a sharp spike at the beginning of the 2003 period where the CPI reached a level of 275. After that, the graph shows some sharp declines, but with a long-term upward trend until 2016. Future predictions show that the CPI will fluctuate with a downward trend until 2023, then will rise again to reach a level of around 150 in 2024.

3.5. Evaluation

The final step is to compare the predictions of each model to assess their accuracy in capturing inflation and CPI patterns. This comparison helps identify the most appropriate and reliable model in reflecting historical trends and future projections. The results of the evaluation of the three models are presented in Table 1.

Table 1. Comparative Evaluation Results of the Three Models

Model	Data	MAE	MSE	RMSE
SARIMA	Inflation	1,43	3,25	1,80
	CPI	16,71	450,9	21,23
SVR	Inflation	1,53	2,72	1,64
	CPI	14,01	374,79	19,35
LSTM	Inflation	6,23	53,38	7,30
	CPI	11,55	191,76	13,84

Based on Table 1, the SVR model performs best at predicting inflation, with the lowest MAE, MSE, and RMSE values among the models. SARIMA comes in second with a higher error rate, while the LSTM model records the highest error, indicating that SVR is superior in inflation forecasting. Meanwhile, for CPI prediction, the LSTM model produced the lowest error across all three evaluation metrics, followed by SVR. In contrast, SARIMA had the highest error, making it the least effective model for predicting CPI compared to LSTM and SVR.

4. CONCLUSION

This study successfully implemented and compared three time series forecasting models, SARIMA, SVR, and LSTM, in predicting inflation in Indonesia using historical data. The results demonstrate that each model has distinct strengths depending on the characteristics of the data. SVR achieved the best performance in inflation prediction, as evidenced by the lowest error values, thanks to its ability to capture nonlinear relationships effectively. SARIMA showed stable performance, particularly in handling seasonal patterns, while LSTM demonstrated its ability to model complex temporal dependencies, especially for CPI data.

Furthermore, the findings indicate that no single model universally outperforms others across all types of economic data. LSTM provided superior results in CPI prediction, while SARIMA was less effective in handling highly volatile data. This confirms that model selection should be tailored to the dataset's structure and behavior to achieve optimal forecasting performance.

For future research, it is recommended to explore hybrid or ensemble models that combine the strengths of statistical and machine learning approaches, such as SARIMA-SVR or SARIMA-LSTM. Additionally, incorporating external variables (e.g., exchange rates, interest rates, and global economic indicators) may further improve prediction accuracy. Expanding the dataset and applying advanced hyperparameter optimization techniques are also suggested to enhance model robustness and generalization.

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